Mixed-Initiative Control for Collaborative Countermine Operations

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Key Words

Military de-mining, mixed-initiative, collaborative workspace, adjustable autonomy, performance and evaluation

Abstract

This paper discusses experimental results achieved by using mixed initiative robot behavior to address the challenges of detecting and marking buried metal landmines. Mission requirements pertaining to communication bandwidth and operator workload precluded conventional approaches to communication and tasking. Instead, a framework for sharing control and communicating "behavior intent" was developed to coordinate activities of intelligent unmanned air and ground vehicles. To alleviate dependence on global positioning, collaborative tasking tools were developed that use common reference points in the environment to correlate disparate internal representations (e.g. aerial imagery and ground-based occupancy grids). The behaviors allow each team member to act independently while communicating environmental features and task intent at a high level. Results show that the resulting system produced a significant decrease in task time to completion and a significant increase in detection accuracy and reliability when compared to the current military baseline. As required, the experiment was accomplished without dependence on global positioning or continuous network communication. These findings indicate that by providing an appropriate means to interleave human and robotic intent, mixed initiative behaviors can address complex and critical missions where neither teleoperated nor autonomous strategies have succeeded.

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Introduction

Landmines are a constant danger to soldiers during conflict and to civilians long after conflicts cease, causing thousands of deaths and tens of thousands of injuries every year. It is estimated that more than 100 million landmines are emplaced around the world and, despite humanitarian efforts to address the problem more landmines are being emplaced daily than are being removed [38]. Often humans are used to perform de-mining at great risk to life and limb. The task is extremely dangerous and tedious and human performance tends to vary drastically depending on factors such as fatigue, training, and environmental conditions.

It has long been thought that landmine detection is an appropriate application for robotics because it is a dull, dirty, and dangerous task [2, 24]. However, the reality has been that the critical nature of the task demands a reliability and performance that neither teleoperated nor autonomous robots have been able to provide [23]. Autonomous strategies based on assumptions of accurate positioning and sensor information have proven unreliable. On the other hand, teleoperated strategies are severely limited by the fact that the combined demands of navigation, sweep coverage and signal interpretation severely overload the human operator.

In response to these shortcomings, we will present a mixed-initiative approach that has been developed that allows air and ground vehicles as well as remote human operators to work together to accomplish a countermine mission. Researchers at the Idaho National Laboratory (INL), working with Carnegie Mellon University (CMU), and the Space and Naval Warfare

Systems Center (SSC), San Diego have developed a system that combines the bird's eye perspective from an unmanned aerial vehicle with behavior-based autonomous search and detection capabilities on a ground robot to identify and mark buried landmines. The effectiveness of the resulting system was rigorously evaluated by the Army Test and Evaluation Command (TECO) and by the U.S. Army Maneuver Support Center (MANSCEN) at Ft. Leonard-Wood.

Although the formal countermine mission requirements made no explicit reference to the level of autonomy required for the task, the research reported here indicates that operational success was possible only through the use of a mixed-initiative approach that defined the responsibilities and roles of the human, air vehicle, and ground vehicle. It is important to note that humanitarian de-mining is significantly different from military demining. Antonic, Ban, and Zagar point out that "Military needs to breach a narrow path through the minefield as fast as possible and with acceptable loses due to missed mines. On the opposite side, humanitarian demining requires 100% detection and removal of all mines on large area." [2]. This research uses information from humanitarian de-mining but the task itself is based on military demining.

The paper proceeds as follows. We will first discuss background on using robots for humanitarian demining and mixed initative. Then We will discuss the mission requirements and show how they evolved based on available technology. We then present the solution to the countermine problem on unimproved dirt roads. The system used to solve the countermine problem is then presented and we discuss the experiment and results. Finally, the paper is concluded and directions of future work are provided.

Background

Many research papers describe the challenges and requirements of humanitarian demining along with suggesting possible solutions [2, 24]. Efforts to improve robotic de-mining have resulted in the design of a new system, but have left that system unproven in physical environments [3, 10, 14, 20, 28, 32]. The development of systems without proving their usefulness in domains leaves one to question how effective the solution is in a real situation. In fact, Trevelyan believes that robots cannot be a solution to humanitarian demining because the sensor technology is not sufficient, there are huge varieties of land mines that defy automated solutions, and robots are likely to be too expensive for practical operations in some contries [41]. It is true that automated solutions will be difficult to come by, but perhaps, the focus is on making systems rely too much on automation when a better approach might be to create a system that requires some human and some robot initative.

Many scientists have pointed out that it is clear that benefits are to be gained if robots and humans work together as partners [13, 21, 35, 37]. To successfully accomplish this, the robot must have some level of automation or else it would simply be a remote-controlled vehicle that extends the capabilities of the operator but not have initiative of its own.

Parasuraman et al. observe that "automation does not merely supplant but changes human activity and can impose new coordination demands on the human operator" [30]. They also note that when designing human robot systems, it is important to consider which system functions should be automated and to what extent. Steinfeld [40] also comments that it would be particularly useful to know the the 'optimal' autonomy state for a given task. Determining good levels of robot autonomy for a particular task is an important decision that is often approached by asking which skills the operator and robot have then dividing the task accordingly [19, 31, 35]. The appropriate use of autonomy may stem from an understanding of how and why autonomy behaves [29, 39]. Other views about how the trust of an autonomous robot can be established include making a reliable system, and making the decision processes of the robot more transparent [5].

One solution to provide the appropriate level of autonomy is to provide adjustable autonomy or sliding scale autonomy [4, 6, 11, 15, 16, 33, 36]. These approaches enable the operator to change the level of autonomy with which the robot operates. The challenge with such an approach is that it is often difficult for the operator to know which level of autonomy is the best for the current situation that the robot is in. In fact, this solution requires the operator to have very good situational awareness of the robot, the task, and the environment in order to give correct changes in autonomy at the correct time. This places a huge responsibility on the sholders of the end user as they are required to understand all the levels of automation within the entire system, how to activate and switch between autonomy levels, and when each level is particularly applicable.

In previous user studies it was observed that, for a given task, a particular interface design [25–27] or autonomy configuration [6–8] provided better results than another configuration. Moreover, when end users were given a complete system with multiple, adjustable levels of autonomy and different interface designs, it was difficult for novice robot operators to fully grasp the posibilities of the system or even understand what particular aspects were most beneficial to their success [43].

Towards this end, our solution has been to develop a fixed mixed-initative strategy that requires an understanding of the task and the responsibility of each of the agents in the system beforehand, such that when the task is performed, the tasks for each agent are understood. This approach is different from traditionaly mixed-initative approaches in HCI where attempts to solve a problem occur gradually through collaboration between a human and the system [1, 17, 18, 34].

Mission Requirements

The purpose of this research was to evaluate the effectiveness and suitability of an Autonomous Robotic Countermine (ARCM) System to proof a 1-meter dismounted lane by searching for, marking, and reporting detected landmines and marking the boundaries of the proofed lane. The intent was to provide the current force with an effective alternative to manned dismounted lane countermine operations. MANSCEN determined that although accurate digital marking of landmine locations within a terrain map was desired, accurate physical marking of the mine locations was considered essential for the mission requirements.

To develop a successful solution required a complete understanding of the end-user's goals and requirements. This was accomplished with over two years of dialogue with MANSCEN to develop and refine the mission requirements based on capabilities and limitations of various technologies. Furthermore, numerous conversations with the Night Vision and Electronic Sensor Directorate (NVESD) at Ft. Belvoir were required to discuss the capabilities and limitations of current sensor technologies.

Previous studies by MANSCEN had shown that real-world missions would involve limited bandwidth communication, inaccurate terrain data and sporadic availability of GPS. Consequently, task constraints handed down from MANSCEN demanded minimal dependence on network connectivity (e.g. wireless Ethernet), centralized control (e.g. off-board motion planning), global positioning (GPS), and accurate *a priori* terrain data.

MANSCEN requirements also emphasized the need for reduced operator workload and training requirements. The military operational requirements document (ORD) specified that within the future combat system (FCS) unit of action, there would no longer be dedicated engineers focused on the countermine mission; instead, any soldier within the unit of action should be able to task the system to prove an area or lane from a graphical representation of the local environment.

A final requirement was that the robotic system be able to handle cluttered outdoor environments. Although the robot platforms and sensor suite were important considerations, the goal of this effort was not focused on a particular robot platform or a particular countermine sensor; rather, the stated goal was to "provide portable re-configurable tactical behaviors to enable teams of small UGVs and UAVs to collaboratively conduct semi-autonomous countermine operations."

Mission Scenario

A fundamental challenge with the strict requirements was how to provide a means for the user to task the robot without dependence on either *a priori* terrain data or global positioning. The reason this was difficult is because there is no simple correlation between the operators understanding of the physical world and the robot's digital representation of the world. To operate without dependence on global positioning, the ground robot had the ability to build a digital, occupancy map that could be shared with the human operator. This provided some context for the operator to task the robot however, the context was limited to the parts of the environment that had already been explored by the robot. To improve the operator's ability to task the robot in previously unexplored areas, it was determined that an unmanned air vehicle would be used to survey surrounding terrain, locate potential minefields and provide imagery that could be used for tasking and monitoring while the ground robots perform their search and detection mission.

The mission scenario which emerged included the following task elements.

a. Deploy a UAV to survey terrain surrounding an airstrip.

b. Analyze imagery to identify possible minefields.

c. Use common landmarks to correlate UAV imagery & UGV occupancy map

d. UGV navigates autonomously to possible minefield

e. Perform UGV search behavior to physically and digitally mark mines.

f. Mark dismounted lane through suspect terrain.

This mission scenario posed an interesting mixed-initiative challenge. The military requirement dictated “semi-autonomous control,” meaning that the human must be kept in the loop, but that time spent at the controls should be minimized. No specific requirement was given regarding the nature of tasking or monitoring or what the operator was required to do, just that they had to be there. To orchestrate the operator and robotic initiative, it was necessary to ask some basic questions for each task element. First, it was necessary to consider performance and empirically assess whether the operator or robot was better for each task element. Secondly, it was necessary to consider the workload costs for the operator and the robot since one of the mission requirements was to minimize operator workload. Lastly, the benefit to using the operator or robot for the task was compared against the cost of not using the operator or robot for the task.

Efforts to answer these questions significantly influenced the mixed-initiative framework employed. For example, the visual analysis in element (b) was originally intended to be an automated process, using change detection software that could analyze suspect terrain with no human intervention. In reality, real world experimentation showed that the change detection software, when deployed from unmanned air vehicles, could not reliably ascertain the possible minefield locations. Instead, it was determined that human image understanding was a superior asset and required minimal operator time. Consequently, the mission scenario was modified to allow the human to identify the possible minefields within the mosaiced aerial imagery and task the UGV with either a single click to specify the terminus of a lane or by specifying the vertices of a polygon around a suspected minefield.

The mixed-initiative used to solve the mission requirements was based on determining what tasks should be performed by each of the agents then developing the system to support the performance of the agents for those tasks. Other approaches to mixed-initiative are more interested in a collaboration or cooperative problem solving between agents where a robot and human hold a dialog about a problem [13]. These solutions are most useful when the intelligent system cannot know the operator’s intentions or the goal of the task [18]. However, in this particular research, the task was well defined and the goals well defined. Therefore, our use of mixed-initiative has been to define the tasks for the different agents.

System Components

Our solution for the countermine experiment discussed here builds on several years of spiral development to evaluate and improve robot behaviors and interface tools in support of remote vehicle operation. The solution is applicable because it supports the MANSCEN requirements of minimal dependence on networking, centralized control, GPS, and prior information about the environment. A series of human participant studies have demonstrated that robust robot behaviors and interface methods can provide reduction in operator workload, operator error, communication bandwidth, and can increase task efficiency and the operator’s subjective feeling of control [8]. However, previous experiments were limited primarily to novice users and basic navigation and search tasks. The countermine mission offers an opportunity to apply the results and experiences from our previous user-studies and development on robot behaviors and interface capabilities to a complex, end-to-end mission. To accomplish this in a rigorous field experiment, it was necessary to utilize vehicle platforms, communications, and sensor payloads that could meet the military requirements without assuming away any element of the task.

Air Vehicle Development

The air vehicle of choice was the Arcturus T-15, a low cost, fixed wing aircraft that can maintain long duration flights and carry the necessary video and communication modules. For the countermine mission, the Arcturus was equipped to fly two hour reconnaissance missions at elevations between 200 and 500ft.

Figure 1: The Arcturus T-15 airframe and launcher

A spiral development process was undertaken to provide the air vehicle with autonomous launch and recovery capabilities as well as path planning, waypoint navigation and autonomous visual mosaicing. An air-powered catapault launch system was developed that allows autonomous deployment of the air vehicle. After launch, a waypoint list is executed which allows the air vehicle to fly a coverage pattern over the airstrip and autonomously collect and mosaic real-time overhead aerial imagery. Unfortunately, the mosaiced imagery was not accurate enough to meet the requirements for this mission; therefore, single images were used to correlate the visual imagery with the robot occupancy grid.

Ground Vehicle Development

Carnegie Mellon University developed two ground robots for this effort which were modified humanitarian demining systems equipped with inertial systems, compass, laser range finders and a low-bandwidth, long range communication payload. A MineLab F1A4 detector, which is a standard issue mine detector for the U. S. Army, was mounted on both vehicles along with an actuation mechanism that can raise and lower the sensor as well as scan it from side to side at various speeds. A force torque sensor was used to calibrate sensor height based on sensing pressure exerted on the sensor when it touches the ground. The mine sensor actuation system was designed to scan at different speeds to varying angle amplitudes throughout the operation. SPAWAR developed a compact marking system that dispenses two different colors of agricultural dye. Green dye was used to mark the lane boundaries and indicate proved areas while red dye was used to mark the mine locations. The marking system consists of two dye


Figure 2: Countermine robot platform

tanks, a larger one for marking the cleared lane and a smaller one for marking the mine location. The system also included pumps, hoses and nozzles for dispensing the dye, and a control system that linked to the INL Robot Intelligence Kernel (RIK).

The Robot Intelligence Kernel (RIK) supports behaviors for navigation, search and detection [12]. The behaviors include reactive primitives such as guarded motion and obstacle avoidance and increase in complexity to deliberative capabilities such as path planning and area coverage. Throughout this spectrum, the level of autonomy that is possible increases with the layering of behaviors. For instance, to accomplish the overall countermine search behavior, the RIK must arbitrate between obstacle avoidance, waypoint navigation, path planning and mine detection coverage behaviors, all of which run simultaneously and compete for control of the robot. (Charts in Appendix A and B illustrate the interactions between components of the RIK.)

The RIK provides adjustable autonomy including the four modes of interaction shown in Figure 3: High-Level Tasking Mode, Shared Mode, Safe Mode and Teleoperation [12]. *Teleoperation* involves direct human control where the robot takes no initiative. *Safe Mode* where the robot takes initiative only to protect itself, *Shared Mode* where the human and robot may both take initiative, and *High-Level Tasking Mode* where the human may only provide high level input throughout the task. The robot may also be configured for a “fully autonomous” mode such that the robot, upon startup, proceeds to explore the environment and detect mines with no human input whatsoever. Note that each of these modes may be used to accomplish the countermine task. In fact, the dynamic autonomy offered by the RIK provides users with an ability to task the system differently depending on the task constraints such as available operator workload and communication connectivity.

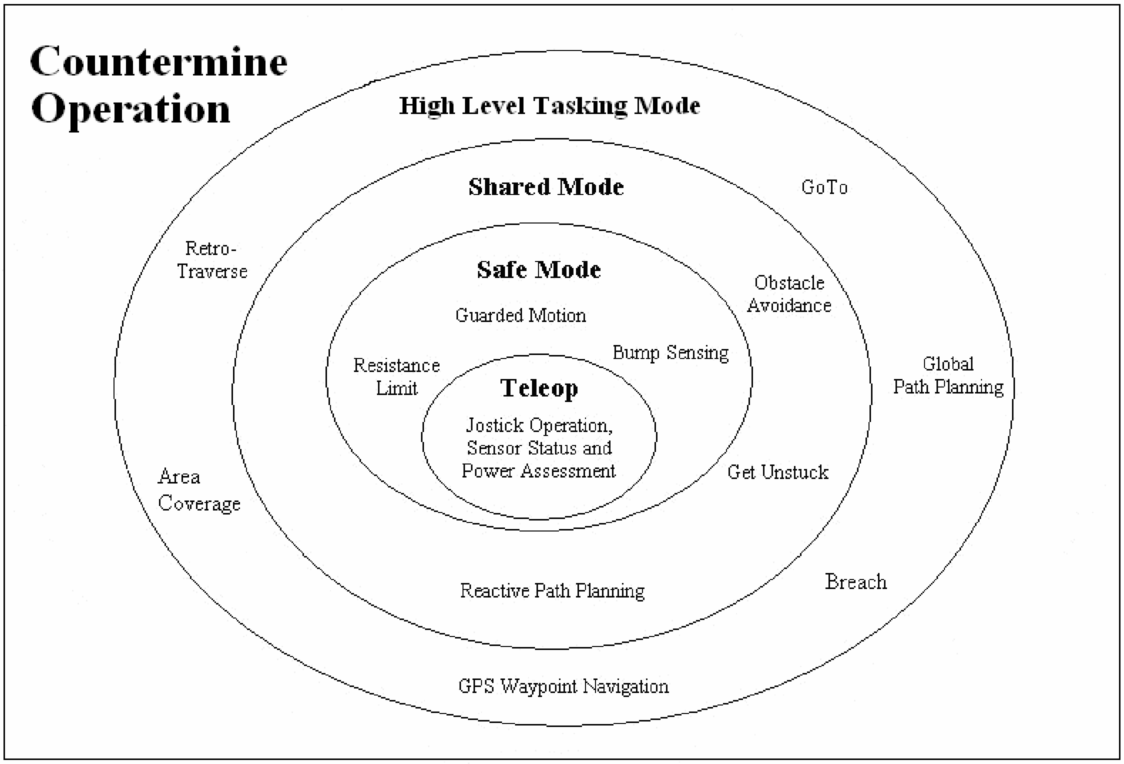

Figure 3: Four modes of operator control and the behaviors that support them

Mode of Autonomy	Defines Task Goals	Supervises Vehicle Direction	Motivates Motion	Prevents Collisions
Teleop	*Human*	*Human*	*Human*	*Human*
Safe	*Human*	*Human*	*Human*	*Robot*
Shared	*Human*	*Human*	*Robot*	*Robot*
HLTasking	*Human*	*Robot*	*Robot*	*Robot*
Autonomous	*Robot*	*Robot*	*Robot*	*Robot*

Figure 4: Initiative Chart

The chart shows how these different levels of interaction provide specific modes of mixed-initiative control. An important aspect of this research was determining how to combine initiative from the human and robot. At times, the robot must be able to refuse human control such as when the mine sensor is engaged and the human is controling the robot motion directly, the robot should be able to limit its speed in order to safely detect mines and avoid obstacles. An important goal was to facilitate sharing responsibilities between robot and operator such that the user could provide input without interfering with the robot's ability to navigate, avoid obstacles, plan paths, and detect land mines. For this countermine experiment, High-Level Tasking Mode was configured to limit the possibility for human input to disrupt robot behaviors such as area coverage or mine marking. Previous studies using High-Level Tasking Mode indicates that appropriately constraining human initiative can improve task efficiency, reduce operator workload and limit instances of operator confusion and frustration [3]. Supporting mixed-initiative in this way actually increases users' feeling of control by taking control away from them at the right times. In this sense, the goal is not to blindly "mix" initiative, but rather to define responsibilities that avoid conflict and optimize task allocation.

Interface Development

For the majority of robotic operations, video remains the primary means of providing information from the remote environment to the operator [9]. Woods et al. describe the process of using video to navigate a robot as attempting to drive while looking through a 'soda straw' because of the limited angular view associated with the camera [42]. If teleoperation is problematic for simple navigation tasks, it is even less appropriate for the countermine mission where navigation is only one aspect of a complex operation.

Unlike traditional interfaces that require transmission of live video images from the ground robot to the operator, the representation used for this experiment uses a 3D, computer-game-style representation of the real world constructed on-the-fly [26]. The digital representation is made possible by the robot implementing a map-building algorithm and transmitting the map information to the interface. To localize within this map, the RIK utilizes Consistent Pose Estimation (CPE) developed by the Stanford Research Institute International [23]. This method uses probabilistic reasoning to pinpoint the robot's location in the real world while incorporating new range sensor information into a high-quality occupancy grid map. When features exist in the environment to support localization, this method has been shown to provide approximately +/- 10 cm positioning accuracy even when GPS is unavailable.

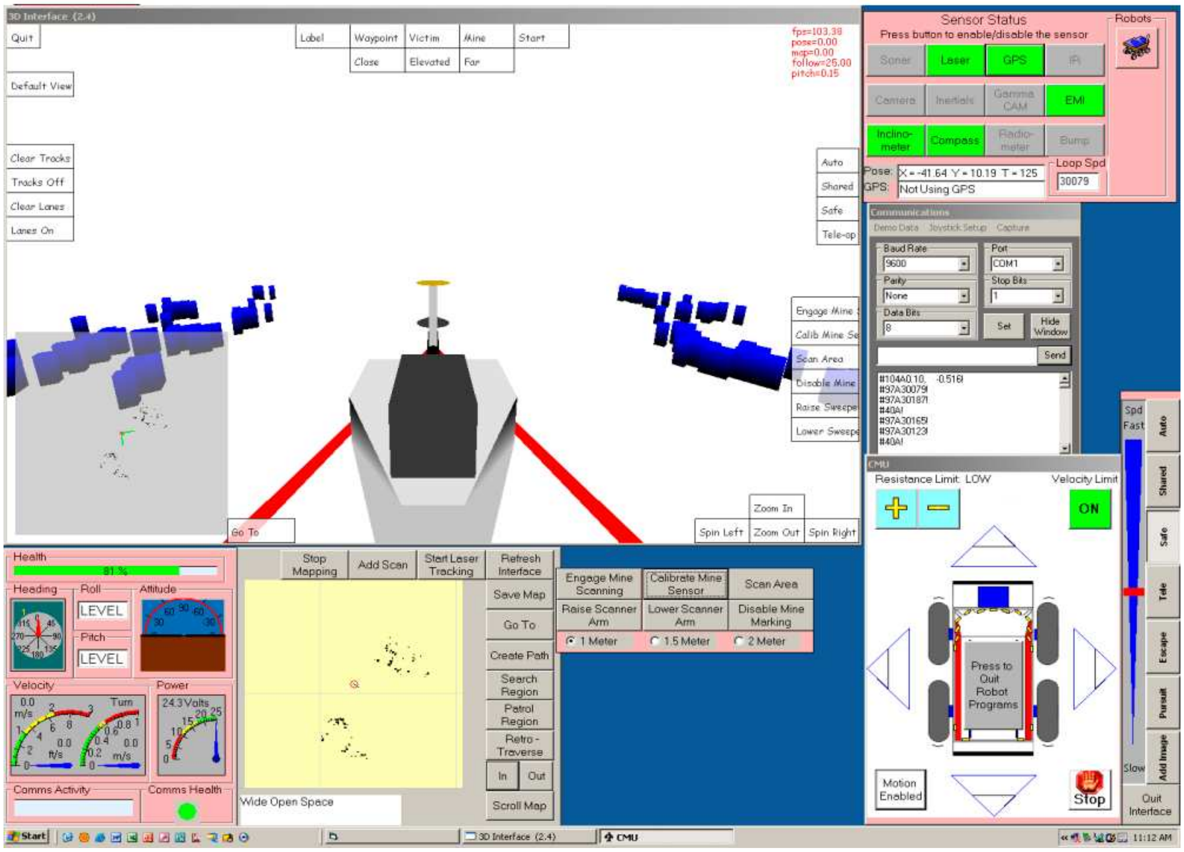

Figure 5: The Operator Control Interface is comprised of a number of windows displaying information about the robot and its environment, including an easy to use computer-game-style interface.

The 3D representation also maintains the size relationships of the actual environment and the robot, helping the operator understand the relative position of the robot in the real world. By changing the zoom, pitch and yaw of the digital representation, the operator can use multiple perspectives, including egocentric views that show the environment from the perspective of a particular robot as in Figure 5, to exocentric views that show a top-down view of the entire environment as in Figure 6. Previous HRI studies at the INL have shown that different perspectives can be used to support different autonomy modes [8].

The default configuration of the interface used to interact with the ground robots consists of a single touch screen display containing re-sizeable windows as shown in Figure 5. The upper right-hand window contains sensor status indicators and controls that allow the operator to monitor and configure the robot's sensor suite as needed. The lower right-hand window pertains to movement within the local environment and provides indications of robot velocity, obstructions, resistance to motion, and feedback from contact sensors. The interface indicates blockages that impede motion in a given direction as red ovals next to the iconographic

Figure. 6: The Interface above shows a seamless fusion of UGV terrain mapping, GPS and real-time aerial imagery from an autonomous unmanned air vehicle.

representation of the robot wheels. Since the visual indications can sometimes be overlooked, a force feedback joystick was also implemented to resist movement in the blocked direction. The joystick vibrates if the user continues to command movement in a direction already indicated as blocked. At the far right of the window the user can select between different levels of robot autonomy.

The interface supports the ability to input aerial imagery into the 3D window. The interface will automatically correlate geo-referenced imagery with the robot occupancy grid if GPS is available on the robot. However, countermine requirements stated that geo-referenced imagery may not be available. Even with geo-referenced imagery, real world trials showed that the GPS based correlation technique does not reliably provide the accuracy needed to support the countermine mission. In most cases, it was obvious to the user how the aerial imagery could be nudged or rotated to provide a more appropriate fusion between the ground robot's digital map and the air vehicle's image. As a result, correlation tools were developed that allow the user to select common reference points within both representations. Examples of these common reference points include the corners of buildings, fence posts, or vegetation marking the boundary of roads and intersections. In terms of the need to balance human and robot input, it was clear that this approach required very little effort from the human (a total of 4 mouse clicks) and yet provided a much more reliable and accurate correlation than an autonomous solution.

To facilitate initiative throughout the task, the interface must not only merge the perspectives of robotic team members, but also communicate the intent of the agents. For this reason, the tools used in High Level Tasking were developed which allow the human to specify coverage areas, lanes or target locations. Once a task is designed by the operator, the robot generates an ordered waypoint list or path plan in the form of virtual colored cones that are superimposed onto the visual imagery and map data. The placement and order of these cones updates in real time to support the operator's ability to predict and understand the robot's intent. Using a suite of click and drag tools to modify these cones the human can influence the robot's navigation and coverage behavior without directly controlling the robot motion.

Experiment

To test the proposed system and the mission requirements, an experiment was conducted October 20-28, 2005 at the INL's UAV airstrip by personnel from the US Army MANSCEN and the TECO, both based at Ft. Leonard Wood, Missouri. The U.S. Army TECO authored the experiment plan, performed the field experiments and certified all data collected. The experiment consisted of repeated trials of a dismounted route proving task, and data collected included measurements of human, robot and overall team performance of the resulting system. Proofing a dismounted lane required the robot to navigate a path to a target location while physically and digitally marking detected mines and the boundaries of the searched lane. A test lane was prepared on a 50 meter section of an unimproved dirt road near the INL UAV airstrip because the wheeled UGV's cross country mobility is limited. Six inert A-15 anti tank (AT) landmines were buried on the road between six and eight inches deep. Note that six landmines in a 50 meter section is considered a high mine concentration. Sixteen runs were conducted with no obstacles on the lane and 10 runs had various obstacles scattered on the lane such as boxes and crates as well as sagebrush and tumble weeds.

Procedure

The robot was prepared for operation at the beginning of each trial. Each trial consisted of the operator positioning the robot at the starting point of the lane, manually setting the mine sensor to the correct height, and starting the mine scanning and marking behaviors on the robot. Since the repeated use of colored dye would produce confusion regarding the marks on the ground, water was used instead of dye throughout the trials. As the robot proceeded, test personnel following the robot placed poker chips at the location of each wet spray mark with red poker chips. These poker chips allowed personnel to accurately measure distance from the center of the dye spray to the center of mine as shown in Figure 7. The water mark then dried before the next trial. Throughout the experiment all mine locations reported to the OCU were checked and a copy of the data log and a screen shot of the markings from the OCU were saved. A photograph of each mine and their location was taken and a video of each run was recorded. Data sheets recorded meteorological data, mine marking errors, missed mines, false detections, and other comments from those conducting the experiment. After the robot had completed its mission, it was driven back to the start point by the operator. Maintenance was conducted on the robot between trials. At the conclusion of the trial the distance from each mine mark to the center of the mine was measured and recorded.

Figure 7: Examples of Mine Marking and Burying a Mine

Results

There were four criteria to the tested requirements in this experiment: finding mines, marking mines, reporting mines, and marking proofed lanes. During the 26 runs executed during the experiment the robot correctly detected 124 mines. Over the course of the experiment, seven mines in the lane were not detected. The overall success rate for detecting mines was 95%. Of the seven mines not detected two were due to a miscalibration of the height of the sensors, two were due to low battery levels on the sensor, and three were not detected during sharp turns to avoid obstacles. All missed mines were at or near the edge of the proofed lane. ARCS had a single false detection during all the runs. One mine was detected and reported twice, once on the leading edge of the mine and once on the trailing edge. This gives a false detection rate of <1%.

All of the mines detected by ARCM System were physically marked on the ground. The distance between the center of the physical mark and the center of the mine was measured for 91 mines as shown in Appendix C. The average marking error was 12.67 cm with a standard deviation of 8.56 cm. The mine diameter was 33.4 cm. For each of the trials, the proven lane was marked in the physical and digital environments as shown in Figures 8 and 9.

Of the 124 mines detected only one mine was not digitally reported to the OCU, the remainder rest were automatically reported and logged. A text file with the UTM coordinates of each mine was logged in a separate run file and screen shots of each run were made showing the location of each mine as it relates to the robots internal map (see Figure 8).

The ARCM System was successful in all runs in autonomously negotiating the 50 meter course and marking a proofed 1-meter lane. The 26 runs had an average completion time of 5.75 minutes with a 99% confidence interval of +/- 0.31 minutes. The maximum time taken was 6.367 minutes. Interestingly, the presence of obstacles on the course seemed to improve the speed at which the robot performed. Closer examination of the data showed that the speed up was not due to the obstacles, but rather to the fact that the trials with obstacles were performed on a wider stretch of road. The navigation behaviors in the RIK allowd the robot to move faster since the boundaries of the road were further apart. On the 16 runs without obstacles the average time to complete was 6.058 minutes with a 99% confidence interval of 0.216 minutes. The 10 runs with 7 obstacles on the course showed an average completion time of 5.267 minutes with a 99% confidence interval of 0.585 minutes.

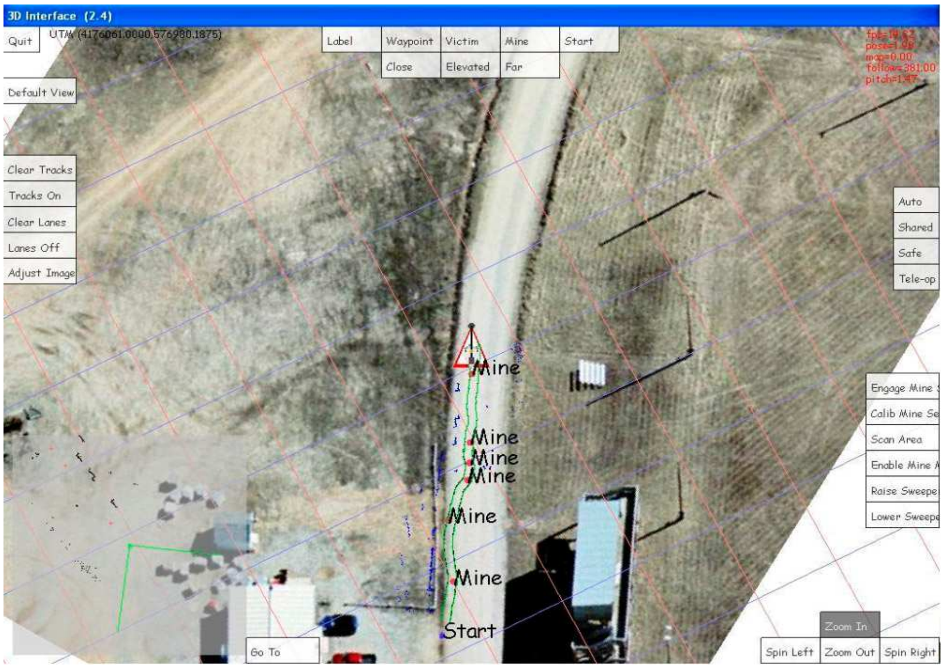

Fig. 8: Mine and Proofed Lane Display on OCU.

Figure 9: Proofed Lane Marking

When comparing the robot to current military operations, the MANSCEN at Ft. Leonard Wood reports that it would take approximately 25 minutes for a trained soldier to complete the same task accomplished by the robot, which gives about a four-fold decrease in cycle time without putting a human in harm's way. Furthermore, a trained soldier performing a counter-mine task can expect to discover 80% of the mines. The robotic solution raises this competency to 95% mine detection.

Another interesting finding pertained to human input is that the average level of human input throughout the countermine exercises was less than 2% when calculated based on time. The TECO of the U.S. Army indicated that the ARCM System achieved "very high levels of collaborative tactical behaviors." When the MANSCEN applied the "Autonomy Levels for Unmanned Systems" rubric, which includes indices for operator interaction, environmental difficulty and task complexity, to evaluate the overall autonomy of the system, a level of 8-9 was applied out of a possible 10.

Conclusion

The results of a rigorous, real-world experiment showed that the proposed autonomous robot countermine system performed admirably accurately marking, both physically and digitally, 124 out of 131 buried mines in an average time of less than six minutes.

While these results are encouraging, it is important to understand that the challenges of countermine operations have by no means been completely solved. One important caveat to the work reported here is that the mines used had a high metallic content. The need to find low-metallic mines will require a more advanced sensor. Ongoing collaboration with the NVESD at Ft. Belvoir will result in a combined ground penetrating radar and electromagnetic induction sensor which could be used in the next phase of this effort to improve mine sensing of low-metallic mines. Another important caveat is that the robot platform used for the effort reported here does not meet the military's need for ruggedization or for all-terrain mobility rather, the presented tests were performed on an "unimproved dirt path." To accomplish the same task in cross-country terrain is also a subject of future work.

Finally, the U.S. Army Engineer School indicated that the next phase of research should support a vertical float feature to maintain an exact height of the sensor head above the ground and that they would like to see more collaborative UAV functions including terrain data and uses as a communication relay.

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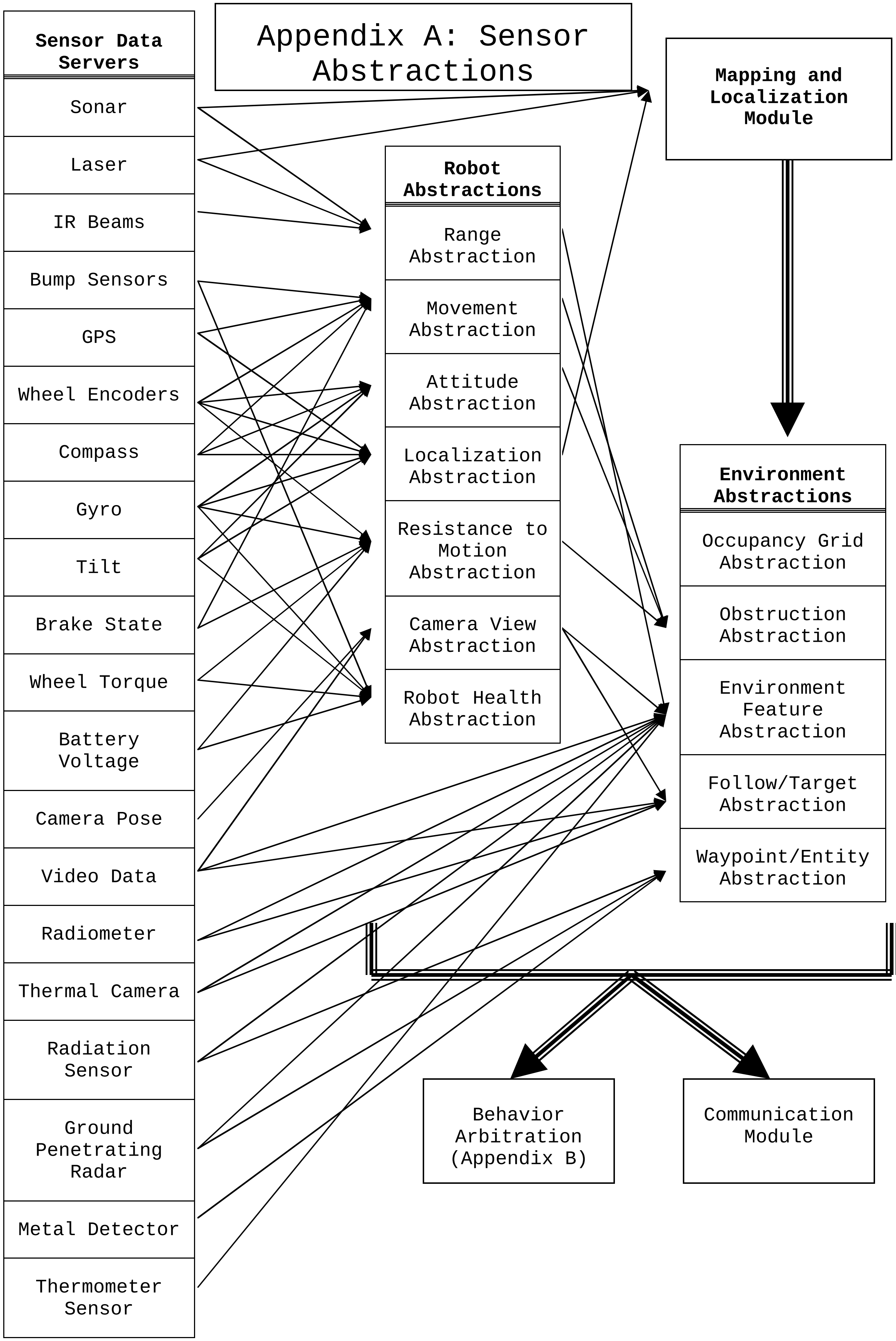
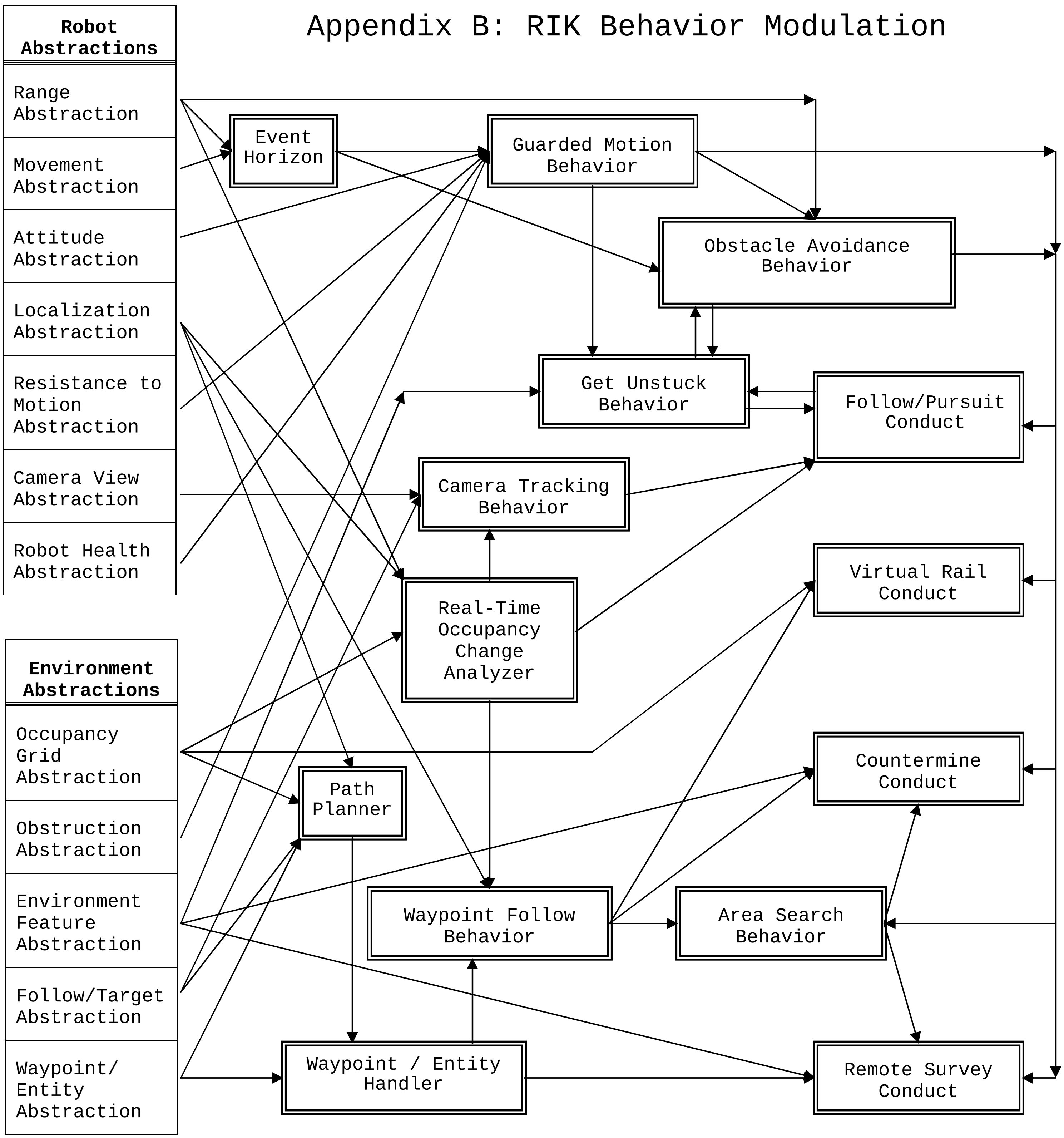
Appendix A: Sensor Abstractions



Appendix B: RIK Behavior Modulation



APPENDIX C: A table showing mine marking accuracy for the first 91 mines found.

	Mine #1 Marking cm Error	Mine #2 Marking cm Error	Mine #3 Marking cm Error	Mine #4 Marking cm Error	Mine #5 Marking cm Error	Mine #6 Marking cm Error
	10	8	7	15	20	Miss
	23	8	24	4	0	7
	6	16	10	7	17	16
	4	8	7	20	1	3
	13	0	Missed	13	5	0
	15	15	20	15	0	10
	12	8	12	0	0	7
	12	16	18	19	15	15
	1	8	16	8	8	Missed
	26	18	15	14	4	24
	7	28	27	31	33	21
	20	39	17	26	22	26
	3	16	5	13	9	8
	12	23	5	12	0	15
	16	0	0	4	4	22
	16	18	Missed	20	12	Missed
# of Marks	**16**	**16**	**14**	**16**	**16**	**13**
Average	**12.25**	**14.31**	**13.07**	**13.81**	**9.38**	**13.38**
St Dev	**7.09**	**10.06**	**7.84**	**8.24**	**9.76**	**8.29**
CI (+/-) 99%	**5.22**	**7.41**	**6.31**	**6.07**	**7.19**	**7.02**